Energy Policy 123 (2018) 525–532

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Accessing provincial energy efficiencies in China's transport sector

Chunping Xie[a], Mengqi Bai[b], Xiaolei Wang[c,*]

[a] Birmingham Centre for Energy Storage, School of Chemical Engineering, University of Birmingham, Edgbaston, Birmingham B15 2TT, UK
[b] Nuclear Engineering, School of Physics & Astronomy, University of Birmingham, Edgbaston, Birmingham B15 2TT, UK
[c] School of Management, China University of Mining and Technology, Xuzhou, Jiangsu 221116, China

ARTICLE INFO

Keywords:
Transport sector
Energy efficiency
Energy-saving potential
Stochastic frontier analysis

ABSTRACT

The transport sector is attracting increasingly attention in the context of climate change and sustainable development, for its rapidly growing demand for energy and heavy reliance on oil products. Especially in China, where the demands for transportation are tremendous and ever-increasing, it is worthy to explore the provincial variations in energy efficiency in the transport sector, in order to enhance energy efficiency and to promote energy savings in this sector. By using stochastic frontier analysis (SFA) approach, this paper calculates the provincial energy efficiency as well as energy saving potential in China's provincial transport sector over 2007–2016. Results suggest that China's national average energy input efficiency in the transport industry is 0.673 during the sample period, which implied that relatively large degree of non-efficiency exists in this sector. Besides, the increase of government support (GS), the improvement of road condition (RC) and public transport (PT) are influencing factors for the improvement of China's provincial energy efficiency in the transport industry. Additionally, energy saving potential in the transport sector is also estimated in this paper. It is shown that, although energy efficiency in the eastern China is the highest (much higher than the country-wide level), the estimated absolute amount of the energy saving potential in the eastern area is significantly larger than those in the central area and western area due to the fact that the eastern area contributes to the largest share of the total energy consumption in this sector.

1. Introduction

Transport sector is crucial to economic and social development, as mobility is generally known as one of the basic and vital needs for human. It provides moving from one location to another for passengers and frights, and expedites the economic activities in the industrial world (Atabani et al., 2011). A sophisticated mobility system plays a role as a catalyst in the development of economy.

However, in recent years, transport sector consumes a high portion of total primary energy globally (Ong et al., 2011). Energy use in transport sector is growing especially fast in the emerging countries like China and part of Latin America (Yan and Crookes, 2007). Based on the statistics from Asia Pacific Energy Research Centre (APERC), energy consumption in China's transport industry raised from 15.0 Mtoe in 1980 to 166.5 Mtoe in 2010 (i.e., with a growth rate of 8.4% per annual), which made transport one of the fastest growing sectors in terms of energy consumptions. According to Wang et al. (2014), the global energy consumption in transport sector accounted for one-third of the world's consumption in 2013, while such a proportion in China reached 20%.

Moreover, the world is currently facing the challenge of global warming and environmental pollution in consequence of continuous growth in energy use. Emissions and pollutants produced by different economic sectors have negative impact on the environmental protection, sustainable development and the public health (Mahlia, 2002). The transport sector, among the entire economic sectors, has been seen as one of the main contributors to the environmental degradation and the deterioration of human health due to its excessive reliance on fossil fuels and high greenhouse gas (GHG) emissions (Pucher et al., 2005; Gasparatos et al., 2009; Liu et al., 2013; etc.).

With more and more attentions being paid on environmental problems and energy issues worldwide, evaluating environmental performance and energy efficiency has become crucial (Zhou et al., 2014; Wang et al., 2018b). Energy efficiency as well as energy-saving potential in transport sector are addressing increasing attention worldwide, which are significant for relieving energy shortage and improving the environment (Xie and Hawkes, 2015; Xie et al., 2016).

The remainder of this article is divided into the following sections: Section 2 presents a literature review; Section 3 describes methodologies and data processing in the manuscript; Section 4 discusses the

* Corresponding author.
E-mail address: xiaoleiwang@cumt.edu.cn (X. Wang).

https://doi.org/10.1016/j.enpol.2018.09.032
Received 20 June 2018; Received in revised form 20 September 2018; Accepted 23 September 2018
Available online 01 October 2018
0301-4215/

model findings; and Section 5 concludes the paper and provides policy implications.

2. Literature review

Why improving energy efficiency is of significant? According to Cullen et al. (2011), the improvement of energy efficiency could contribute to relieving energy shortage, saving energy costs, and reducing CO_2 emissions. Patterson (1996) elaborated different kinds of definitions and indicators on energy efficiency. According to Lovins (2004), energy efficiency is defined as the ratio of the product (including any value or service) supplied to the energy that needed to supply it.

"Broadly, any ratio of function, service, or value provided to the energy converted to provide it." It is well known that there are plenty of indicators measuring energy efficiency. According to Hu and Wang (2006), these indicators are simply concluded as two types: one is the partial factor energy efficiency (PFEE) index, the other is the total-factor energy efficiency (TFEE) index.

PFEE mainly measures the relationship of energy input and energy output, and energy is usually regarded as an input factor during the production process. PFEE index simply denotes a proportional relation between energy input and output without considering the contribution of other production factors like capital and labor to the output generation, as a result, it has been criticized in recent years. Given this, Hu and Wang (2006) raised the category of TFEE for the first time. Under the frame of neo-classical production theory, TFEE takes into consideration not only the energy factor, but also the production factors of labor and capital, when evaluating energy efficiency. In addition, the substitution effects between different input factors are also included in the efficiency analysis. The framework of TFEE can be summarized as follows: (i) Firstly, defines the production possibility set (given production technology level); (ii) Secondly, builds a production frontier using the input and output data of each decision-making unit; (iii) Finally, analyzes the relationship between each production unit and the production frontier. When a production unit deviates from the production frontier, it suggests that resources in this production unit have not been fully utilized and there is room for Pareto improvement. To be specific, TFEE is regarded as the ratio of the theoretically minimum energy input to the real energy input. After Hu and Wang (2006), a wide variety of literature conducted empirical analysis on the energy efficiency performance in many countries/areas using different TFEE indexes, among which the data envelopment analysis (DEA) and the stochastic frontier analysis (SFA) are the most popular research methodologies. Both DEA and SFA are frontier approaches on the basis of distance function (Coelli et al., 2005). The measured efficiency is a relative efficiency, which is strongly comparable within the sample but has poor comparability among different samples.

The basic idea of DEA is to describe the production possibility set by using the smallest convex set. The frontier of production possibility set is a technological frontier, which reflects the optimum production state under given technology level. In practice, DEA builds the technological frontier by linear programming technique, thus to determine the evaluation benchmark and conduct the efficiency analysis. From this prospective, DEA is a nonparametric approach with following advantages: (i) it does not require an assumed form of production function or distance function, which can avoid the risk of model misspecification; (ii) the flexible setting of DEA model (with many types) can be applied to the estimation of most efficiency evaluation models. As a result, DEA is widely used in the estimation of TFEE. In spite of the above-mentioned advantages, DEA has obvious disadvantages. DEA model does not take into consideration the impacts of statistical error and other random errors, and is easily affected by the quality of sample data. As a result, there may be deviation in the efficiency estimation.

Given that considerable statistical noise may exist in macroeconomic data, the frontier method of SFA is recommended to overcome this problem. For example, Boyd (2008) and Zhou et al. (2012) built a SFA model to estimate the energy efficiency on the basis of energy distance function. DEA regards the deviation part between decision-making unit and the technological frontier, as inefficiency. Different from DEA, SFA divides this deviation part into two sections: one section is caused by inefficiency; while the other is caused by random errors. Therefore, SFA can measure energy efficiency while eliminating the impact of statistical noise. In addition, as a parameter estimation approach based on statistics, SFA allows statistical tests for model settings. Due to the advantages mentioned above, SFA has been widely applied into evaluating national/industrial energy efficiency performance.

For example, Filippini and Hunt (2012) adopted SFA to analyze the residential energy efficiency of the United States over 1995–2007. Hu and Honma (2014) estimated energy efficiency for the ten industries in the fourteen developed countries for the time period of 1995–2005 based on SFA. By adopting panel data parametric frontier technique, Honma and Hu (2014) measured energy efficiency in Japan. Lundgren et al. (2016) estimated the energy efficiency and energy demand in Swedish manufacturing sectors in a company level through the SFA technique. Based on the input-oriented Shephard distance function, He (2011) constructed to a SFA model and conducted an empirical study on energy efficiency and its impact factors for China's 36 industrial sectors over 1994–2008. The results suggested the average industrial efficiency was 0.76 over the research period, and the opening-up policy was a contributing factor for the increase of energy efficiency while the state-owned property right was the opposite. Lin and Du (2013) measured China's provincial energy efficiency over 1997–2010, by utilizing the SFA approach similar to Zhou et al. (2012). Lin and Wang (2014) adopted SFA to analyze energy efficiency in the iron & steel sector in China. By using a similar method, Lin and Long (2015) evaluated energy efficiency in the chemical sector in China. Ouyang et al. (2018) measured factor price distortions and estimate their impact on energy efficiency based on an empirical analysis of 30 provinces of China using the SFA.

There are also many papers focusing on the meta-frontier which could take regional heterogeneity into consideration. For example, Feng and Wang (2017) analyzed the total-factor energy efficiency and energy savings potential in China's provincial industrial sectors by using a meta-frontier DEA. Wang et al. (2018a) evaluated carbon reduction efficiency of technologies on project level through employing a meta-frontier DEA approach.

On the basis of distance function, this paper builds a stochastic frontier model regarding excessive energy input, to estimate the energy input efficiency and the corresponding energy-saving potential, as well as the influencing factors in China's provincial transport sectors.

When measuring the energy-saving potential, a proper benchmark is that the given energy service level cannot be degraded, which means to reduce the amount of energy consumption on the premise of achieving at least the same level of output; or in other words, to achieve equivalent or more energy services with the same amount of energy input. The frontier analysis based on distance function provides a practicable approach for measuring energy input efficiency under given output (different from the energy efficiency represented by energy intensity) and energy-saving potential.

3. Method and data

3.1. Methodology

Referring to Zhou et al. (2012), a production possibility set (T) that reflects the production technology is built in our paper. Three factors including labor (L), capital (K) and energy (E) are taken as input factors, while the gross domestic product (Y) is viewed as the single output.

$$\mathrm{T} = \{(L, K, E, Y)\colon Input\,(L, K, E)\, is\ able\ to\ provide\, Y\} \tag{1}$$

We define the Shephard energy distance function as follows, in

order to estimate the energy efficiency from the perspective of production frontier.

$$D_E(\mathrm{L, K, E, Y}) = \sup\left\{\alpha : \left(\mathrm{L, K}, \frac{\mathrm{E}}{\alpha}, \mathrm{Y}\right) \in \mathrm{T}\right\} \tag{2}$$

When translog form is adopted to approximate the Shephard energy distance function, we can get the following equation:

$$\begin{aligned} lnD_E(E_{it}, L_{it}, K_{it}, Y_{it}) = {} & \beta_0 + \beta_E lnE_{it} + \beta_L lnL_{it} + \beta_K lnK_{it} + \beta_Y lnY_{it} \\ & + \beta_T ln\mathrm{T} + \beta_{EL}(lnE_{it}{*}lnL_{it}) + \beta_{EK}(lnE_{it}{*}lnK_{it}) \\ & + \beta_{EY}(lnE_{it}{*}lnY_{it}) + \beta_{LK}(lnL_{it}{*}lnK_{it}) \\ & + \beta_{LY}(lnL_{it}{*}lnY_{it}) + \beta_{KY}(lnK_{it}{*}lnY_{it}) \\ & + \beta_{ET}(lnE_{it}{*}T) + \beta_{LT}(lnL_{it}{*}T) + \beta_{KT}(lnK_{it}{*}T) \\ & + \beta_{YT}(lnY_{it}{*}T) + \beta_{EE}(lnE_{it})^2 + \beta_{LL}(lnL_{it})^2 \\ & + \beta_{KK}(lnK_{it})^2 + \beta_{YY}(lnY_{it})^2 + \beta_{TT}(T)^2 + V_{it} \end{aligned} \tag{3}$$

Where V_{it} is a random variable with a normal distribution, which accounts for the statistical noise. Eq. (3) can be further written as the following equation due to the linear homogeneity of the Shephard distance function in terms of energy inputs,

$$\begin{aligned} lnD_E(E_{it}, L_{it}, K_{it}, Y_{it}) = {} & lnE_{it} + lnD_E(1, L_{it}, K_{it}, Y_{it}) = lnE_{it} + \beta_0 + \beta_L lnL_{it} \\ & + \beta_K lnK_{it} + \beta_Y lnY_{it} + \beta_T ln\mathrm{T} + \beta_{LK}(lnL_{it}{*}lnK_{it}) \\ & + \beta_{LY}(lnL_{it}{*}lnY_{it}) + \beta_{KY}(lnK_{it}{*}lnY_{it}) \\ & + \beta_{LT}(lnL_{it}{*}T) + \beta_{KT}(lnK_{it}{*}T) + \beta_{YT}(lnY_{it}{*}T) \\ & + \beta_{LL}(lnL_{it})^2 + \beta_{KK}(lnK_{it})^2 + \beta_{YY}(lnY_{it})^2 \\ & + \beta_{TT}(T)^2 + V_{it} \end{aligned} \tag{4}$$

Re-arranging Eq. (4), the following equation is obtained,

$$\begin{aligned} -lnE_{it} = {} & \beta_0 + \beta_L lnL_{it} + \beta_K lnK_{it} + \beta_Y lnY_{it} + \beta_T ln\mathrm{T} + \beta_{LK}(lnL_{it}{*}lnK_{it}) \\ & + \beta_{LY}(lnL_{it}{*}lnY_{it}) + \beta_{KY}(lnK_{it}{*}lnY_{it}) + \beta_{LT}(lnL_{it}{*}T) + \beta_{KT}(lnK_{it}{*}T) \\ & + \beta_{YT}(lnY_{it}{*}T) + \beta_{LL}(lnL_{it})^2 + \beta_{KK}(lnK_{it})^2 + \beta_{YY}(lnY_{it})^2 + \beta_{TT}(T)^2 \\ & + V_{it} - U_{it} \end{aligned} \tag{5}$$

Where, $U_{it} = lnD_E(E_{it}, L_{it}, K_{it}, Y_{it})$ is a non-negative variable that denotes the level of energy inefficiency.

Beside the time trend variable T, which represents technology changes over time; several explanatory variables to energy inefficiency are also taken into account, including government support (GS), road condition (RC) and public transport(PT). Industry scale (IS), ownership structure (OS), degree of openness (DO) are widely accepted as explanatory variables to the inefficiency function when analyzing efficiency of input factors in many industrial sectors (such as He (2011)). However, explanatory variables in this paper are quite different from those researches focusing on industrial sectors, considering transport industry is a service industry. Government support (GS), road condition (RC) and public transport (PT) are chosen as explanatory factors to the energy inefficiency function due to the following reasons:

(i) Government support (GS)
The local facilities and standard of traffic system is determined to a great extent by the level of financial investment to transport industry provided by the local government, as a result affect energy efficiency in transport industry of this area. Government support is supposed to have a negative correlation with the energy inefficiency of local transport industry.

(ii) Road condition (RC)
Road transport is the largest part in transport sectors, and there is a positive correlation with the energy efficiency of road transport according to Lin and Xie (2013), who also suggested transportation on high-classified highway can save more energy than on low-classified highway. Gao (2007) noticed that current average speed on expressway can be 80–100 KM/H, leading to more than 20% of oil consumption saved comparing to driving on normal highway. He and Zhu (2009) found out road condition plays a decisive role in influencing oil consumption of vehicles. Based on former researches, road condition is supposed to have a negative correlation with the energy inefficiency of transport industry in this paper.

(iii) Public transport (PT)
The convenience for the local residents taking public transportation depends on the developing level of public transit. Energy can be saved by choosing public transportation rather than private vehicles. Generally, the average annual per capita times for taking public transportation in an area (which means the annual passenger volume of public transportation divided by total number of local residents) represents the developing level of public transport, and has a negative correlation with the energy inefficiency of transport industry.

Therefore, Eq. (5) can be written as follows,

$$\begin{aligned} -lnE_{it} = {} & \beta_0 + \beta_L lnL_{it} + \beta_K lnK_{it} + \beta_Y lnY_{it} + \beta_T ln\mathrm{T} + \beta_{LK}(lnL_{it}{*}lnK_{it}) \\ & + \beta_{LY}(lnL_{it}{*}lnY_{it}) + \beta_{KY}(lnK_{it}{*}lnY_{it}) + \beta_{LT}(lnL_{it}{*}T) \\ & + \beta_{KT}(lnK_{it}{*}T) \\ & + \beta_{YT}(lnY_{it}{*}T) + \beta_{LL}(lnL_{it})^2 + \beta_{KK}(lnK_{it})^2 + \beta_{YY}(lnY_{it})^2 \\ & + \beta_{TT}(T)^2 \\ & + \beta_{GS}lnGS + \beta_{RC}lnRC + \beta_{PT}lnP\mathrm{T} + V_{it} - U_{it} \end{aligned} \tag{6}$$

According to Eq. (6), based on the estimations of the parameters in the likelihood function, the energy efficiency at time t can be obtained by:

$$EEI_{it} = E[exp(-U_{it})|e_{it}] \tag{7}$$

Accordingly, energy saving potential can be estimated through:

$$\mathrm{ESP}_{it} = E_{it}(1 - EEI_{it}) \tag{8}$$

3.2. Data processing

Panel data of transport industry of China's 29 provinces or municipalities over 2007–2016 are selected as the research sample in the empirical study (Tibet and Chongqing are not included because of data deficient), which are mainly collected from China's provincial statistical yearbooks, China's energy statistical yearbooks, and official publications from national statistical bureau, ministry of finance, and departments of transportation. All variables about value are converted to comparable price based on 2007. The main variables considered in this manuscript are stated as follows.

(i) Output (Y)
For many decades now, transport researchers (see e.g. Ashton (1947)) have considered that transport, whether passenger or freight, is mainly a derived demand, that the value to us of passenger-km and tonne-km is that they satisfy some human need. In this respect, transport service can be regarded as the output that transport sector provides. In other words, the only product that transportation provides is its services, by satisfying passengers' need or creating added value for freight. As a result, the traffic turnover volume, a comprehensive measuring indicator reflecting the sum of passenger services and freight services provided by various modes of transportation, is chosen to evaluate the total output of the transport sector. Due to the incomparability of the passenger turnover volume (unit: passenger-km) and the freight turnover volume (unit: tonne-km), we need to convert the passenger turnover volume to the freight turnover volume according

to the converting ratios of passenger to freight of railway, highway, waterway and aviation set in China's statistical system (please refer to Lin and Xie (2013) for more details).

(ii) Energy input (E)

Data on energy consumptions in China's transport sector at the provincial level could not be separated from the official statistical indicator (the indicator of 'energy consumption in transport, postage & storage industries'), since the data of energy consumption in the transport sector are reported aggregately with energy consumption in the postage and storage industries in '*China's statistical yearbooks*'. However, considering that postage and storage industries only take up a very small share in the total energy consumption in transport, postage & storage industries, this indicator of 'energy consumption in transport, postage & storage industries' is therefore regarded as the energy consumption in the transport sector. Data of the provincial energy consumption from 2007–2016 are collected from the CCIE database. All data on energy consumption are converted into coal equivalent using the converting coefficient in '*China's energy statistical yearbook*'.

(iii) Capital input (K)

The perpetual inventory method (PIM) is adopted to construct capital stock of the transport sector in each province of China. According to PIM, capital stock can be evaluated by the following equation:

$$K_t = (1-\delta_t)*K_{t-1} + I_t \tag{9}$$

Where K_t represents the level of capital stock that need to be evaluated in time t; K_{t-1} represents the level of capital stock in time t-1; while I_t denotes capital investment in time t; and δ_t represents the depreciation rate in time t. In order to calculate the level of capital stock in time t, there are four main steps: a.) Decide a base year with given level of capital stock; b.) Find out the amount of capital investment of each year at its current price; c.) Convert the capital investments at current price to constant price according to the corresponding price index; d.) Estimate the rate of depreciation. On the ground of previous researches and experience, we adopt the similar method as in Wu et al. (2008), based on their calculation of capital stock in transport industry over 1980–2005, to estimate the provincial capital stock in transport industry over 2007–2016.

(iv) Labor input (L)

Data of China's provincial employees in transport industry over 2007–2016 are collected from CCIE database.

4. Model results and discussions

4.1. SFA model results

Table 1 shows the SFA model results.

From the results it can be observed that all coefficients of the three explanatory variables are significant. Coefficient of government support

Table 1
Final model estimations.

Variable	coefficient	t-value	Variable	coefficient	t-value
Constant	−9.008	−1.01	T*T	0.01	2.40
LnY	1.19	1.99	T*LnY	−0.01	−1.11
LnK	0.18	0.10	T*LnK	−0.04	−1.32
Lnl	−0.35	−0.29	T*Lnl	0.05	2.71
LnY*LnK	−0.16	−2.33	LnGS	−0.10	−1.91
LnY*Lnl	0.21	4.62	LnRC	−0.07	−1.45
LnK*Lnl	−0.07	−0.43	LnPT	−0.17	−4.00
LnY*LnY	0.00	−0.04	t	−0.10	−2.71
LnK*LnK	0.11	0.98	sigma-squared	0.08	7.71
Lnl*Lnl	−0.14	−1.80	gamma	0.91	20.80
T	0.09	0.35	log likelihood function	35.56	

(GS) is negative (-0.102), which means the increase of financial investment from the local government contributes to the enhancement of energy efficiency in the transport industry and the influence is significant. The estimated coefficient of road condition (RC) is negative (-0.068), suggesting the improvement of road condition contributes to the increase of energy efficiency in local transport industry. Coefficient of public transport (PT) is also negative (-0.172), but is a little bigger than coefficients of GS and RC in absolute value, indicating a relatively higher influence of the public transport development on the improvement of energy efficiency in the transport sector. Finally, the coefficient of trend variate T reflects the non-efficiency dynamic change, which indicates the energy input efficiency in transport industry has a time varying trend of slight decrease year by year. These results are in accordance with the reality in China.

The above results suggest that: the energy efficiency in China's transport industry can be improved by increasing local financial investment, improving road conditions and developing public transport. Among which, public transport (PT) is the most significant influencing factors, with the largest coefficient in absolute value. It indicates that developing comprehensive public transport is an effective measure to solve the problem of low energy efficiency in transport industry. Currently, public transport in China is far from enough to meet the needs of resident trips and economic development, with a very low trip rate of public transport in many cities. Through increasing public transport, it contributes to essentially relieving traffic congestion, promoting energy conservation and emission reduction. The second largest influencing factor is government support (GS). The financial investment in transport sector contributes to the application of advanced technologies, the construction and improvement of local infrastructures, and the formation of an effective traffic management system, which are of significant to reducing energy consumption in transport industry.

4.2. Energy efficiency in China's provincial transport sector

Energy input efficiency and the corresponding energy-saving potential in transport industry in China's different regions can be calculated, according to the estimated results of our model provided above. Energy input efficiency indicates the degree of the departure from minimum energy input to actual energy input under premise of given output level. If the energy input efficiency equals 1, that means the actual energy input is reasonable and there is no room for energy saving; while if the energy input efficiency is less than 1, that would indicate the existence of excessive energy input and the potential for energy saving. As a result, energy-saving potential in this paper is defined as the amount of energy input that can be saved through improving technical efficiency and moving towards the production frontier. The energy input efficiencies of 29 provinces or municipalities in China over 2006–2017 are listed in Table 2.

In order to make a reasonable comparison and analysis, 29 provinces are divided into groups. In the light of the economic development level as well as the geographical location, the mainland area of China is usually divided into three economic zones: the Eastern, Western, and Central areas. The formation of these three areas is not simply through administrative division or geographical division, but is more related to the national economic development policies. The official classification of the three areas was first presented in the '*7th Five-Year Plan of China (1986–1990)* ', and the characteristics of each area are defined as: (i) the eastern area mainly includes coastal provinces and cities, with a higher economic growth rate as well as more foreign direct investments; (ii) compared to the eastern area, the central regions has a lower economic growth rate and an enormous population, and it is a home base for farming; (iii) the western area mainly includes some economic less-developed regions with lower population density. Based on the official classification, 29 administrative regions (except Tibet and Chongqing on account of data deficient) are distributed as Table 3. Please refer to Yu et al. (2012) and (He and Duchin, 2009) for

Table 2
Provincial energy efficiency in transport industry over 2007–2016.

Area	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Beijing	0.58	0.69	0.76	0.80	0.90	0.92	0.91	0.92	0.94	0.95
Tianjin	0.27	0.42	0.43	0.55	0.73	0.57	0.57	0.65	0.71	0.80
Hebei	0.27	0.32	0.36	0.45	0.55	0.57	0.61	0.61	0.63	0.77
Shanxi	0.32	0.53	0.58	0.59	0.64	0.67	0.72	0.74	0.80	0.85
Inner Mongolia	0.44	0.52	0.64	0.77	0.90	0.96	0.81	0.85	0.90	0.66
Liaoning	0.45	0.49	0.57	0.72	0.82	0.87	0.76	0.85	0.94	0.96
Jilin	0.37	0.41	0.45	0.51	0.59	0.60	0.86	0.91	0.92	0.92
Heilongjiang	0.36	0.35	0.38	0.40	0.66	0.74	0.83	0.91	0.93	0.93
Shanghai	0.59	0.73	0.83	0.94	0.93	0.80	0.87	0.87	0.92	0.96
Jiang	0.31	0.41	0.47	0.60	0.69	0.77	0.74	0.81	0.88	0.91
Zhejiang	0.32	0.40	0.46	0.56	0.65	0.67	0.76	0.81	0.90	0.93
Anhui	0.27	0.29	0.34	0.42	0.50	0.67	0.66	0.77	0.83	0.86
Fujian	0.32	0.43	0.48	0.57	0.64	0.62	0.62	0.70	0.76	0.84
Jiangxi	0.25	0.26	0.30	0.40	0.52	0.59	0.58	0.64	0.73	0.78
Shandong	0.57	0.63	0.75	0.86	0.95	0.97	0.75	0.81	0.85	0.89
Henan	0.28	0.31	0.39	0.48	0.59	0.62	0.68	0.69	0.77	0.79
Hubei	0.52	0.59	0.61	0.73	0.89	0.89	0.83	0.83	0.86	0.95
Hunan	0.40	0.38	0.47	0.58	0.67	0.61	0.80	0.88	0.95	0.97
Guangdong	0.57	0.68	0.75	0.85	0.92	0.91	0.90	0.88	0.93	0.95
Guangxi	0.41	0.43	0.51	0.57	0.65	0.71	0.60	0.76	0.84	0.90
Hainan	0.35	0.62	0.71	0.84	0.93	0.94	0.89	0.91	0.85	0.80
Sichuan	0.45	0.53	0.62	0.64	0.72	0.69	0.44	0.55	0.53	0.71
Guizhou	0.41	0.55	0.63	0.74	0.87	0.93	0.83	0.88	0.91	0.94
Yunnan	0.45	0.52	0.57	0.72	0.82	0.90	0.86	0.94	0.94	0.96
Shaanxi	0.40	0.48	0.59	0.66	0.76	0.81	0.68	0.69	0.70	0.64
Gansu	0.35	0.41	0.49	0.59	0.68	0.72	0.88	0.89	0.88	0.84
Qinghai	0.20	0.26	0.34	0.43	0.51	0.54	0.47	0.56	0.56	0.63
Ningxia	0.47	0.51	0.52	0.70	0.74	0.72	0.73	0.81	0.87	0.91
Xinjiang	0.45	0.48	0.51	0.59	0.69	0.77	0.78	0.85	0.94	0.95

Table 3
Classification of 29 provinces in China.

Three areas	Provinces
Eastern	Shandong, Fujian, Beijing, Hainan, Guangdong, Hebei, Liaoning, Tianjin, Zhejiang, Shanghai, Jiangsu
Central	Hubei, Heilongjiang, Anhui, Shanxi, Henan, Hunan, Jilin, Jiangxi
Western	Inner Mongolia, Gansu, Qinghai, Yunnan, Sichuan, Guizhou, Guangxi, Xinjiang, Shaanxi, Ningxia

more details about regional disparities in China.

Based on Table 2, the average energy efficiency as well as the total energy saving potential of the transport sector in each region over 2007–2016 are calculated as follows (see Table 4).

During the 10 years from 2007 to 2016, the average energy input efficiency in China's transport sector was 0.673, which implied that relatively large degree of non-efficiency exists in China's transport sector. This result is in line with China's extensive development mode of high energy consumption and heavy pollution during the research period. Meanwhile, it is very closed to the results using DEA method, obtained by Chang et al. (2013). By adopting the non-radial DEA model, they analyzed environmental efficiency in China's transport sector. They concluded that in China, most of the provinces did not perform eco-efficiently. In other words, China's transport sector is environmentally very inefficient in general.

Table 4 shows the potential energy savings in different regions of China. The total energy use in transport sector over 2007–2016 was about 2928.842 Mtce, and the potential energy saving was 783.769 Mtce. That is to say, the total potential energy saving accounted for around 26.68% of the total transport energy use.

Based on the three regional groups defined in Table 3, Fig. 1 illustrates the provincial variations in energy efficiency in China's transport sector.

Observing from the variation trend, the average energy input efficiency of Chinese transport industry fell in 2011, bottoming out in 2013, and then it started to increase thereafter. The energy efficiency

Table 4
The energy efficiency & saving-potential in different regions (2007–2016).

		Average energy efficiency	Total energy saving potential
Eastern area	2007	0.42	63.18
	2008	0.53	56.10
	2009	0.60	48.32
	2010	0.70	37.64
	2011	0.79	28.19
	2012	0.78	30.05
	2013	0.76	33.76
	2014	0.80	29.28
	2015	0.85	21.37
	2016	0.89	15.94
Central area	2007	0.34	30.48
	2008	0.39	30.58
	2009	0.44	29.39
	2010	0.51	27.58
	2011	0.63	23.52
	2012	0.67	22.66
	2013	0.75	20.88
	2014	0.80	17.40
	2015	0.85	13.61
	2016	0.88	11.01
Western area	2007	0.40	27.83
	2008	0.47	27.10
	2009	0.54	24.91
	2010	0.64	21.68
	2011	0.73	16.24
	2012	0.78	13.98
	2013	0.71	18.10
	2014	0.78	15.64
	2015	0.81	13.44
	2016	0.82	13.95
China	2007–2016	0.67	783.77

Note: the energy input efficiency of each region is an average value over the period 2007–2016; while energy-saving potential is the accumulation of energy savings in each region over the period (unit: million ton of standard coal).

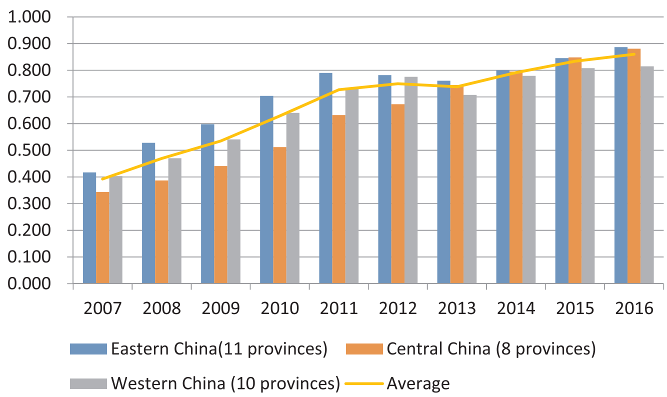

Fig. 1. Comparison on energy efficiency in different areas of China.

ranking from high to low is: the eastern, the central and the western region, with an increasing trend in the energy efficiency gaps among different regions. The energy efficiency in the eastern area was above the national average and the difference was increasing; while the energy efficiency in the western region was below the national average level and the difference was increasing as well.

The eastern China: according to Fig. 1, energy efficiency in this area was significantly above the national average level. Among the 11 provinces and cities in the eastern area: Shanghai, Beijing and Guangdong showed the best energy efficiency performance, with an average energy efficiency during 2007–2016 reaching 0.843, 0.836 and 0.833, respectively. The average energy efficiency in Tianjin city was the lowest, with the value of merely 0.568.

The central China: energy efficiency in the central area was much closed to the national average level, which was lower than the eastern area but much higher than the western area.

The western China: energy efficiency in the western area was amongst the lowest; especially in Qinghai, with an average energy efficiency during 2007–2016 of 0.450.

4.3. Energy-saving potential in China's provincial transport industry

Fig. 2 suggests that,

(i) The energy-saving potential of each region showed a trend of gradual decreasing, implying that: with the economic development and the improvement of living standard, the energy saving technologies for transportation had led to an increasing of energy efficiency.
With further implementations of the '12th Five-year Plan' and the targets/polices regarding energy-saving and carbon emission mitigation, energy efficiency in transport sector has been improved significantly. It is noted that although the eastern area took lead in regard to energy efficiency performance, the absolute amount of energy input in this region was much larger than the other two regions.

(ii) Energy efficiency was relatively lower in the central area and western area, and therefore there was larger room for energy saving in these areas. Though energy efficiency in the central area was higher than that in the western area, the absolute amount of energy saving potential in the central China during 2007–2016 was no less than that in the western China due to the difference in energy inputs in these two areas. According to Fig. 2, energy saving potential in the central area approximately equaled that in the western area.

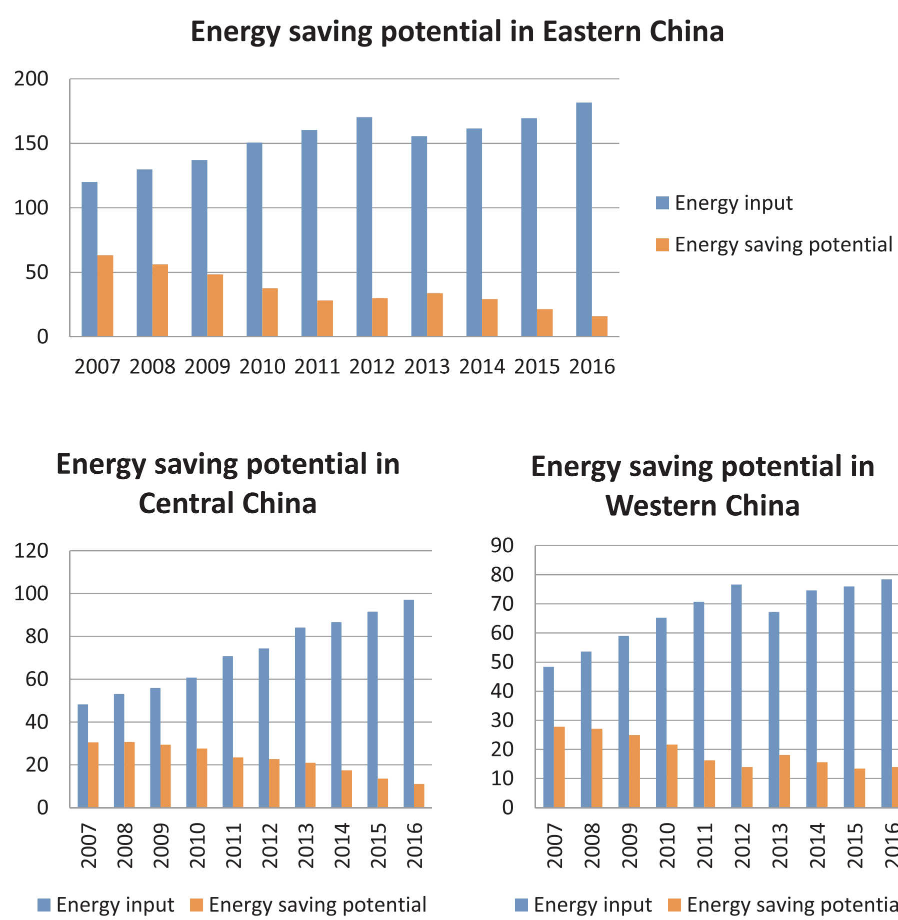

Fig. 2. Energy saving potential in different regions.

Lin and Zhang (2017) evaluated the energy efficiency in China's service sector under meta-frontier technologies and their results suggested that the energy efficiency in the eastern region is the highest, while the energy efficiency in the western region is the lowest. In fact, many studies focusing on China's regional energy performance have suggested that the eastern region performs best in energy efficiency (Zhang et al., 2015), environmental efficiency (Chen and Jia, 2017) and many other efficiency indicators (Fan et al., 2017). The reason is due to the fact that the eastern region enjoys a more developed economy which enables it to promote the diffusion of energy-efficient technologies. Besides, with the rapid economic growth of the eastern region, constraints of resources and environment to economic development have become increasingly prominent, which make these provinces have greater incentive to improve energy efficiency. Besides, Lin and Zhang (2017) found that in the year of 2013, the energy efficiency in China's service sector was 0.801 in the eastern region, 0.551 in the central region, and 0.491 in the western region; respectively. Our study showed that in 2013 the energy efficiency in the transport sector was 0.76 in the eastern region, 0.75 in the central region, and 0.71 in the western region; respectively. It can be seen that larger gaps in provincial energy efficiency exist in the service sector; however, in the transport sector, the differences on energy efficiency among provinces are much smaller.

5. Conclusion and suggestion

Transport energy efficiency has been at the fore front in the expanded notion of energy efficiency, partly because, historically, different modes with very different characteristics have competed to provide passenger and freight services (Moriarty and Honnery, 2012). Given that cars, buses and trains have long been considered alternative modes of passenger transport, their actual or potential efficiency could now be compared on a passenger-km/litre of fuel as well as a seat-km/litre basis. Such comparisons became increasingly common after the 1970s oil crises.

By using Stochastic Frontier Analysis (SFA) approach, this paper calculates the provincial energy efficiency as well as the corresponding energy saving potential over 2007–2016. Results suggest that the average energy input efficiency in the transport sector was 0.673 over the research period, which implied that relatively large degree of non-efficiency exists in China's transport sector. Observing from the variation trend, the average energy input efficiency of Chinese transport industry fell in 2011, bottoming out in 2013, and then it started to increase thereafter.

Our results also suggest government support (GS), road condition (RC) and public transport (PT) are influencing factors for the energy efficiency in transport industry. That is to say, the energy efficiency in China's provincial transport industry is able to be improved by increasing local financial investment, improving road conditions and developing public transport. Among which, public transport (PT) is the most significant influencing factors, with the largest coefficient in absolute value. It indicates that developing comprehensive public transport is an effective measure to solve the problem of low energy efficiency in transport industry.

Energy saving potential in each region in transport sector is also estimated in this paper. It is noted that, although energy efficiency in transport sector in the eastern China was the highest, the estimated absolute amount of the energy saving potential in this sector was significantly larger than those of the central and western areas since it consume the greatest amount of energy.

In light of our findings, the following policy implications are provided for the development of China's transport sector accordingly:

(i) Government support should target at the improvement of infrastructure construction in transport sector to narrow the regional imbalances. In the eastern China, although energy efficiency was relatively higher than other regions, there were still plenty of energy saving potential. Therefore government support on improving infrastructure construction for clean energy utilization, such as the electric vehicle charging pile. While in the western China, energy efficiency can be increased significantly by bringing in more financial investment to improve the local traffic facilities and road conditions
(ii) As public transportation is the most important factor of transportation energy efficiency, encourage the proportion of public transportation can improve energy efficiency and relieve traffic congestion, which is severe especially in the eastern China. To guide the huge traffic population and improve energy efficiency in transport sector, measures can be taken such as imposing restrictions on individual transportations or private vehicles, etc. Government should enlarge the scale of public transportation through encouraging and guiding inhabitants to choose public transportation. Besides, government subsidies are more effective way to improve public transportation.
(iii) Focus on the upgrade of standards of traffic system and vehicle emission. A higher energy efficiency can be achieved by impelling transportation technological innovation and sharing it among different regions. In the eastern China, energy efficiency can be improved further by energy-saving technologies. In the western China, where traffic system is laggard, technical transfer is more convenient to establish traffic system and improve energy conservation.

To sum up, although energy efficiency in China's transportation sector go through substantial improvement, there are still plenty of energy saving potential. At the same time, energy efficiency in eastern, central and western China is different. Therefore, targeted policies should be implemented to improve efficiency and achieve energy conservation in different region. In eastern China, technical innovation and public transportation are more effective to achieve energy conservation, and in western China, technical transfer and infrastructure construction are more urgent to improve energy efficiency.

Acknowledgements

The paper is supported by Natural Science Foundation of Jiangsu Province (no. BK20180664).

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